Uczenie maszynowe i sztuczna inteligencja w finansach Prognoza cen samochodów

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28 stycznia 2024

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1 Biblioteki i dane

notatka

```
[1]: import pandas as pd
    import geopandas as gpd
    from matplotlib import pyplot as plt
    notatka
[2]: df = pd.read csv("otomoto.csv")
    df = df.drop(columns=["OPIS", "OSTATNIA_AKTUALIZACJA"])
    notatka
[3]: df.info()
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 151360 entries, 0 to 151359
    Data columns (total 9 columns):
         Column
                                Non-Null Count
                                                  Dtype
        -----
     0
         TYTUŁ
                                 151360 non-null object
         ROK PRODUKCJI
                                133434 non-null float64
     1
     2
         PRZEBIEG KM
                                133428 non-null float64
     3
         POJEMNOŚĆ SILNIKA CM3
                                151147 non-null float64
         PALIWO
                                 151360 non-null object
     5
         MIASTO
                                 151360 non-null object
                                151360 non-null object
         WOJEWODZTWO
     7
         CENA
                                151360 non-null int64
         WALUTA
                                151360 non-null object
    dtypes: float64(3), int64(1), object(5)
    memory usage: 10.4+ MB
    notatka
[4]: df = df[df.WALUTA != 'EUR']
```

2 Exploratory data analysis

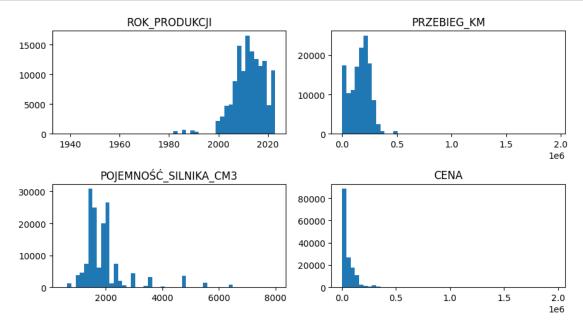
notatka

2.1 Dane numeryczne

```
[5]: df.describe().astype(int)
```

[5]:		ROK_PRODUKCJI	PRZEBIEG_KM	POJEMNOŚĆ_SILNIKA_CM3	CENA
	count	133414	133408	151128	151340
	mean	2012	163790	1937	58185
	std	6	92676	836	65134
	min	1937	1	480	1250
	25%	2009	94296	1469	17900
	50%	2012	179010	1798	35900
	75%	2017	224000	1997	74999
	max	2023	1943000	7990	1966770

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[7]: df.corr(numeric_only=True)

[7]: ROK_PRODUKCJI PRZEBIEG_KM POJEMNOŚĆ_SILNIKA_CM3 ⊔

ROK_PRODUKCJI	1.000000	-0.640512	-0.017783
PRZEBIEG_KM	-0.640512	1.000000	0.087809
POJEMNOŚĆ_SILNIKA_CM3	-0.017783	0.087809	1.000000
CENA	0.609888	-0.641578	0.220893

CENA

 ROK_PRODUKCJI
 0.609888

 PRZEBIEG_KM
 -0.641578

 POJEMNOŚĆ_SILNIKA_CM3
 0.220893

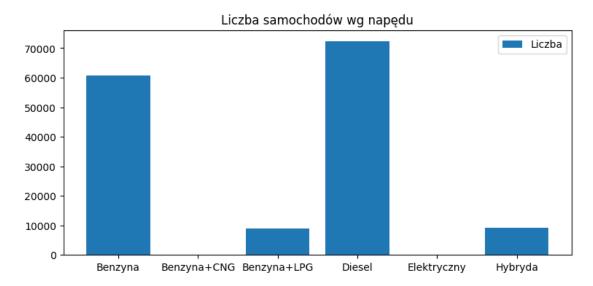
 CENA
 1.000000

notatka

2.2 Dane kategoryczne

notatka

```
[8]: naped = df.groupby("PALIWO")[["CENA"]].count()
  plt.figure(figsize=(9, 4))
  plt.bar(naped.index, naped.CENA)
  plt.legend(["Liczba"])
  plt.title("Liczba samochodów wg napędu")
  plt.show()
```



```
[9]: woj_data = (
          df.groupby("WOJEWODZTWO")
          .CENA.describe()
```

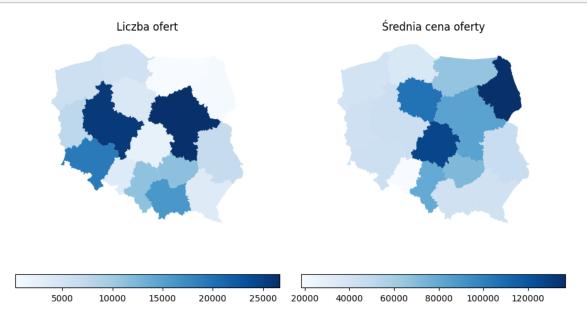
```
.sort_values("count", ascending=False)
     woj_data[["count", "mean", "std"]]
[9]:
                             count
                                        mean
                                                     std
     WOJEWODZTWO
     Mazowieckie
                          26650.0
                                    83636.14
                                               68158.56
                                    44594.14
     Wielkopolskie
                          25600.0
                                               58038.32
     Dolnośląskie
                          19225.0
                                    43793.56
                                               41021.80
     Małopolskie
                          16082.0
                                    42221.08
                                               48355.71
     Świętokrzyskie
                          11331.0
                                    71837.12
                                               30127.82
     Śląskie
                          11193.0
                                    79787.73 108573.26
     Lubuskie
                           7625.0
                                    42991.48
                                               24576.86
     Lubelskie
                                   46321.08
                           6852.0
                                               36391.10
     Zachodniopomorskie
                           5937.0
                                    40753.79
                                               36539.75
     Pomorskie
                           5711.0
                                    36369.68
                                               64280.16
     Kujawsko-pomorskie
                           4163.0 106685.15 126183.36
     Opolskie
                           3721.0
                                    18415.88
                                               28880.51
     Podkarpackie
                           3635.0
                                   41783.20
                                               31857.93
     Łódzkie
                           2468.0 127234.22
                                               81833.37
     Podlaskie
                            825.0 136824.31
                                               80407.67
     Warmińsko-mazurskie
                            320.0
                                    65661.71
                                               69956.99
     Belgia
                              2.0
                                    30749.00
                                                1060.66
     notatka
[10]: woj shp = gpd.read file("wojewodztwa.zip")[["JPT NAZWA ", "geometry"]]
     woj shp.JPT NAZWA = woj shp.JPT NAZWA .str.capitalize()
     notatka
[11]: woj plot = woj shp.merge(
             woj data, how="outer", left_on="JPT_NAZWA_", __

¬right on="WOJEWODZTWO"

         ).dropna().set index("JPT NAZWA ")
[12]: fig, ax = plt.subplots(1, 2, figsize=(9, 5))
      ax1 = woj plot.plot("count", ax=ax[0], legend=True, cmap="Blues",
       →legend_kwds={"orientation": "horizontal"})
     ax1.set axis off()
     ax1.set title("Liczba ofert")
     ax2 = woj plot.plot("mean", ax=ax[1], legend=True, cmap="Blues",
       →legend_kwds={"orientation": "horizontal"})
     ax2.set axis off()
     ax2.set title("Średnia cena oferty")
```

.round(2)

```
plt.tight_layout()
plt.show()
```



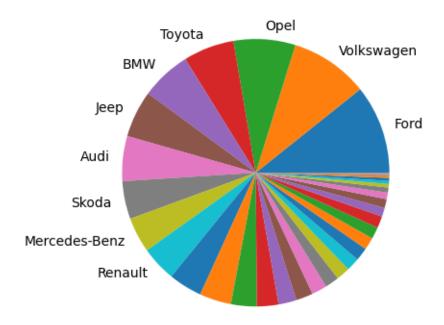
- [13]: df.loc[0, 'TYTUL']
- [13]: 'Skoda Superb 2.0 Comfort'
- [14]: df.insert(1, 'MARKA', df.TYTUŁ.str.split(' ').str[0])
- [15]: marki = df.groupby("MARKA").CENA.describe().round(2).sort_values("count", __ ascending=False)
 marki[['count', 'mean', 'std']].head(10)
- [15]: std count mean MARKA Ford 38581.29 25463.85 16232.0 14343.0 33141.09 33817.38 Volkswagen 19765.17 15144.27 Opel 11316.0 Toyota 28684.19 9312.0 25234.61 BMW 9179.0 99011.68 109428.93 Jeep 8589.0 150863.91 23737.61 Audi 8234.0 115730.76 104048.98 Skoda 6935.0 37460.26 35298.70 Mercedes-Benz 6459.0 104704.07 98882.41

Renault 6456.0 44929.53 27769.33

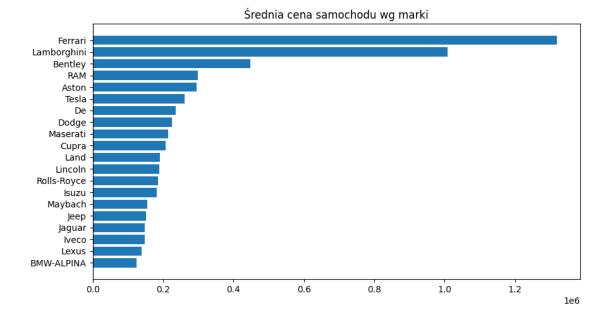
notatka

```
[16]: labels = [label if i < 10 else "" for i, label in enumerate(marki.index)]
    plt.figure(figsize=(6,4))
    plt.pie(marki['count'], labels=labels)
    plt.title('Udział marek w liczbie ofert')
    plt.tight_layout()
    plt.show()</pre>
```

Udział marek w liczbie ofert



```
[17]: marki = marki.sort_values("mean").tail(20)
   plt.figure(figsize=(9, 5))
   plt.barh(marki.index, marki["mean"])
   plt.title("Średnia cena samochodu wg marki")
   plt.tight_layout()
   plt.show()
```



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3 Model

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3.1 Budowa transformatora i predyktora

notatka

```
[18]: from sklearn.preprocessing import StandardScaler, OneHotEncoder from sklearn.compose import ColumnTransformer from sklearn.impute import SimpleImputer from sklearn.pipeline import Pipeline from sklearn.linear_model import LinearRegression from sklearn.metrics import r2_score, mean_absolute_error from sklearn import set_config set_config(display="text")
```

notatka

```
[19]: num_cols = ["ROK_PRODUKCJI", "PRZEBIEG_KM", "POJEMNOŚĆ_SILNIKA_CM3"] cat_cols = ["MARKA", "PALIWO", "WOJEWODZTWO"]
```

pipeline

3.2 Przygotowanie i trening

```
notatka
[21]: from sklearn.model_selection import train_test_split
[22]: df = df.drop(columns=['TYTUL', 'MIASTO', 'WALUTA'])
      y = df.CENA
      x = df.drop(columns=['CENA'])
     dla zobrazowania małe sety danych
[23]: x train, x test, y train, y test = train test split(x, y, train size=0.
       ⇔05, test size=0.01, random state=42)
[24]: default model.fit(X=x train, y=y train)
      pass
     notatka
[25]: from sklearn.metrics import mean absolute error, r2 score
     notatka
[26]: |y_pred = default_model.predict(X=x_train)
[27]: mae = mean_absolute_error(y_train, y_pred)
      r2 = r2_score(y_train, y_pred)
      mae, r2
[27]: (19256.167848500572, 0.744092478959515)
```

3.3 Przeszukiwanie siatki

```
[28]: from sklearn.linear_model import LogisticRegression, LinearRegression
      from sklearn.svm import SVR
      from sklearn.neighbors import KNeighborsRegressor
      from sklearn.tree import DecisionTreeRegressor
      from sklearn.ensemble import RandomForestRegressor
     notatka
[29]: from sklearn.model selection import GridSearchCV
     notatka
[30]: param grid = [
          {"regressor": [LinearRegression()]},
          {"regressor": [LogisticRegression(random state=42)]},
          {"regressor": [KNeighborsRegressor()]},
          {"regressor": [SVR()]},
          {"regressor": [DecisionTreeRegressor(random_state=42)]},
          {"regressor": [RandomForestRegressor(random state=42)]},
      ]
[31]: gscv model = GridSearchCV(estimator=default model, param grid=param grid,
       \rightarrown jobs=-1)
[32]: gscv_model.fit(X=x_train, y=y_train)
      pass
[33]: pd.DataFrame(gscv_model.cv_results_).set_index("rank_test_score").
       ⇒sort index()[
          ["param regressor", "mean test score"]
      ]
[33]:
                                               param_regressor mean_test_score
     rank_test_score
                       RandomForestRegressor(random_state=42)
                                                                        0.938634
      2
                       DecisionTreeRegressor(random state=42)
                                                                        0.909744
      3
                                         KNeighborsRegressor()
                                                                        0.905837
                          LogisticRegression(random state=42)
      4
                                                                        0.873001
      5
                                            LinearRegression()
                                                                        0.731528
                                                         SVR()
                                                                       -0.121414
     znaleziono lepszy randomforestregressor
[34]: y pred = gscv model.predict(x train)
```

```
[35]: mae = mean_absolute_error(y_train, y_pred)
      r2 = r2 score(y train, y pred)
      mae, r2
[35]: (976.0301943302412, 0.9912686902554559)
     notatka
     3.4 Klasyfikator głosujący
     notatka
[36]: from sklearn.ensemble import VotingRegressor
     notatka
[37]: regr = VotingRegressor(
          estimators=[
              ("forest", RandomForestRegressor(random_state=42)),
              ("knn", KNeighborsRegressor()),
              ("tree", DecisionTreeRegressor(random state=42)),
          ],
      )
      voting model = Pipeline([("preprocessor", preprocessor), ("regressor", )

¬regr)])
     notatka
[38]: voting_model.fit(x_train, y_train)
      pass
[39]: y pred = voting model.predict(x train)
[40]: mae = mean absolute error(y train, y pred)
      r2 = r2 score(y train, y pred)
      mae, r2
[40]: (1196.9951266742087, 0.9878689266331786)
     notatka
     3.5 Fine Tuning
     notatka
[41]: param grid = {
          # 'regressor__forest__n_estimators': [50, 100, 200],
          'regressor forest max depth': [None, 5],
          # 'regressor_knn_n_neighbors': [2, 5, 10],
```

```
# 'regressor__tree__max_depth': [5, 25, 50],
          # 'regressor__tree__min_samples_split': [2, 10, 20]
      }
[42]: voting_gscv = GridSearchCV(estimator=voting_model, param_grid=param_grid,__
       \rightarrown jobs=-1)
     notatka
[43]: voting_gscv.fit(x_train, y_train)
      pass
     notatka
[44]: voting_gscv.best_params_
[44]: {'regressor_forest_max_depth': None}
     notatka
[45]: y_pred = voting_gscv.predict(x_train)
[46]: mae = mean absolute error(y train, y pred)
      r2 = r2_score(y_train, y_pred)
      mae, r2
[46]: (1196.9951266742087, 0.9878689266331786)
     notatka
        Podsumowanie
     notatka
 []:
     notatka
         Bibliografia
     notatka
     dane: OTOMOTO.pl
     wpisy do bibliotek:
     - matplotlib - pandas - geopandas - sklearn - numpy
```